The Effect of Income Inequality on Human Development

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Abstract:
Income inequality is how unevenly income is spread across a population. This paper looks at the effects of income inequality on human development through analyzing cross sectional data with multiple linear regression models. The dependent variable in this study is a country's Human Development Index (HDI) in 2018. The primary explanatory variable is a country's Gini coefficient from 2010 – 17. This paper hypothesizes that higher levels of income inequality will have a negative effect on human development as this often results in a misallocation of resources. The models support this hypothesis, but the exact degree of the ceteris paribus effect is still not fully clear.

I. Introduction

Human development is about the robustness of human life. According to the prominent economist Mahbub ul Haq (1999), there is two-dimensional approach to evaluating human development: augmenting human abilities and fostering human development. The former dimension refers to factors like standard of living, life expectancy, and education levels. The latter dimension refers to factors like social equality, human rights, sustainability, and political stability. While there is no single, definite answer to what is human development, it is generally agreed upon that it extends beyond mere economic factors and reaches across a wider range of indicators.

For economic inequality, there are often two primary factors that economists examine: the distribution of income and the distribution of wealth. Unlike human development, there is much more debate on this topic as to what the effects are of higher economic inequality and to what severity those effects are. This paper focuses on income inequality. For income inequality according to Kuznets' (1955) Hypothesis, income inequality starts off at lower levels for pre-industrial societies and increases as industrialization occurs. From this point, Kuznets (1955) thought that income inequality levels would begin to lower as governments adjusted their taxing and welfare programs accordingly. However, income inequality has risen across the globe since the mid-late 20th century, so this issue presses on with importance now more than ever. It is critical to not only examine income inequality but analyze its effects on human development as well.

This paper will uncover the relationship between human development and income inequality through regressing several pertinent variables for both simple and multiple linear regression models. I hypothesize that the relationship between human development and income inequality will be negative. My thought for this relationship is that income inequality actually stunts human development as the greed of the few is detrimental to the many. Income inequality can lead to improperly allocated resources, and education programs, health centers, social initiatives, and more all come at a cost. These resources are the catalysts for human development, so without them, a country's human development is hindered.

II. Literature Review

Mo (2000) studies the effect of income inequality on the economic growth using the Gini coefficient to represent income inequality and GDP growth to represent economic growth. In addition to those two variables, several regression models include other variables such as population growth, average years of schooling for adults over 25, ratio of private investment to GDP, political instability, and others. All variables are percentage changes. In all the models, the coefficients for the Gini variable are negative meaning that income inequality generally had a negative effect on economic growth. Of all the models, income inequality had the largest impact on economic growth when only factoring in schooling years and population growth; a one percent increase in the Gini coefficient signaled a .2162 percent decrease on GDP growth. Mo (2000) concludes with the strong statement that income inequality significantly decreases GDP growth. He goes further and states that income inequality has a direct negative effect on the growth rate of productivity. He suggests that this may be due to an increased lack of trust among the social classes. This distrust leads to higher transaction costs and lower gains from cooperation in addition to many other reasonings.

Haseeb, Suryanto, Hartani, and Jermsittiparsert (2020) research the connection between globalization, income inequality, and human development in Indonesia. To do this, they use a monthly data set from 1990 to 2016 and perform partial and multiple wavelet coherence across several periods ranging from 1-month to 32-month time periods. Globalization is measured through "foreign direct investment and trade … to the GDP ratio" for this study. The coherence between all three variables has significant power regions in shorter time periods, specifically one to twelve months. Their overall analysis of the variables' co-movements across several coherence models leads to several findings. First and foremost, the researchers find that these co-movements change over different time periods. This signals that the short run, medium run, and long run will all behave differently. Furthermore, increasing globalization will increase income inequality. This increase in income inequality decreases human development in turn which they suggest might be due to increased inequality in schooling and labor markets.

Mellor and Milyo (2003) examine the lagged effect of income inequality on public health. They analyze results at both the individual and state-wide level on census data and Current Population Survey data. For the individual analysis, they use a probit model with zero representing poor and one representing fair and lagging the Gini data between five and nine years. Four of the five values had a negative sign indicating that in increase in income inequality led to a decrease in health. However, these results were relatively inconclusive as all values were statistically insignificant when holding individual characteristics and mean state income constant. For state-wide analysis, they lag the Gini data 10 and 20 years across a 30-year time frame. This is a multivariate analysis, and the dependent variables are mortality from cardiovascular disease, malignant neoplasms, homicides, and accidents. When controlling for mean income, age composition, and decade effects, the models suggest that there is a .53 percent increase and .69 percent increase for having any of the four causes of death when lagging for 10 and 20 years respectively. However, all these values are also not significant. This means that the effect of income inequality on public health is limited to none, but the authors stress the importance of not putting too much weight into these results as there are a large number of outside factors too.

There is quite a bit of research that examines the effects of income inequality on a wide range of factors such as economic growth, public health, education levels, and more. However, this paper will look into the effects of income inequality on a composite of these factors – human development. The limited research into the relationship between these two variables is not on international data sets, so the trends identified in those papers may not hold true for the rest of the world. Using an international data set provided by the United Nations will allow a more holistic understanding of how income inequality affects human development. Furthermore, this paper will include numerous secondary explanatory variables to the models: poverty rate, population growth percentage, savings rate, political instability, and Organisation for Economic Co-operation and Development membership. These additional explanatory variables and expanded data sets will allow this paper to offer deeper insights into the relationship between income inequality and human development as has not been done before.

III. Data

The data is collected from multiple sources: The United Nations Development Programme (UNDP), the World Bank, the World Health Organization (WHO), and the Organisation for Economic Co-operation and Development (OECD). All of the data is cross-sectional data, and five of the seven datapoints are from 2018. The two datapoints not from 2018, the Gini coefficient and poverty rate, are collected from the most recent available data in a span ranging from 2011 to 2018. This data has a sample size of 189, and each observation represents a country. The data sources note that the following countries are missing: Democratic People's Republic of Korea, Monaco, Nauru, San Marino, Somalia, and Tuvalu. Only missing 6 countries should not significantly skew the results since this is a minor portion of countries (approximately 3%).

The dependent variable selected was the Human Development Index (HDI) from the UNDP data set. The HDI is a composite measurement of three dimensions: health, education, and standard of living. This measurement is for countries and yields a value ranging from zero to one with higher indices indicating a stronger level of human development; in this paper, HDI has been multiplied by 100 so the values range from 0 to 100 for cleaner analysis. For health, HDI examines life expectancy at birth. For education, it examines mean years of schooling for adults older than 25 and expected years of schooling for children. For standard of living, it examines gross national income (GNI) per capita; however, it uses the logarithm of this value in order to highlight a "diminishing importance of income" (Mahbub ul Haq 1999). For all three measurements, they are indexed and published under the names: health index, education index, and GNI index. These three indices are indexed together to yield the final result – the HDI. This statistic is the golden standard for measuring human development as it is commonly used across research because of its quantitative nature.

The primary explanatory variable selected was the Gini coefficient. The Gini coefficient is a measure of income distribution and represents income inequality; it ranges from 0 to 100. A value of 0 represents a perfect distribution of incomes per household and a value of 100 represents perfect inequality. This statistic was chosen as it is also very commonly used to measure income inequality. The slight drawback is that it measures solely income, not wealth. A scatterplot, Figure 3.1, of the two primary variables displays a negative and mild correlation between the two variables.

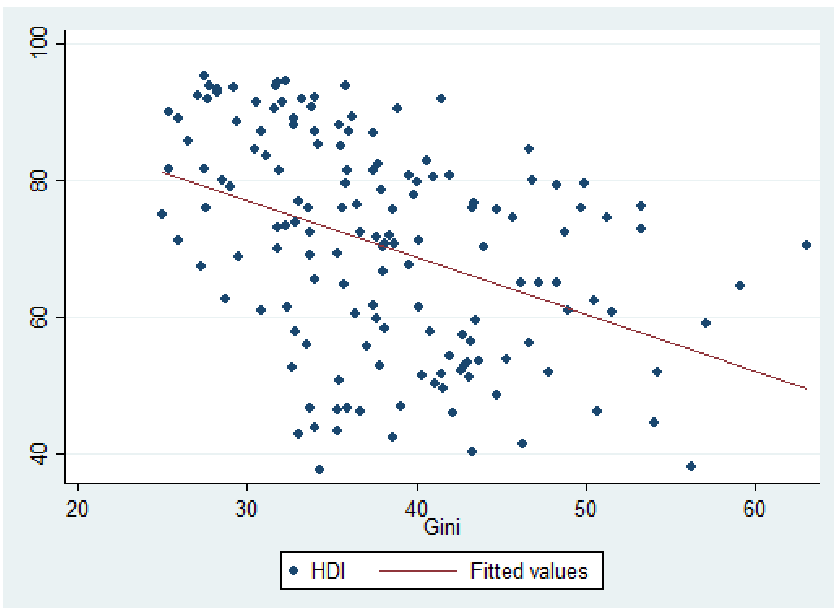

Figure 3.1

Additional explanatory variables were added in to support the models and strengthen the goodness of fit. These are meant to help highlight a more accurate ceteris paribus effect of income inequality on human development from the Gini coefficient and HDI respectively.

The first secondary explanatory variable is the proportion of the population below the international poverty line. The international poverty line is $1.90 income per day for adults; it is set by the World Bank and most recently updated in 2015. This is meant to emphasize the effects of poverty on human development to support income inequality further. This variable is predicted to have a negative coefficient since higher poverty levels intuitively would lead less access to education and healthcare and thus lower human development. The second explanatory variable is the population growth as a percentage of the country from 2017 to 2018. This year was selected since this matches the year of which the HDI data comes from. This is meant to shed light on the effects of population growth on human development as uncontrollable growth can lead to unprepared national infrastructure and government programs. Because of these possibilities, this variable is predicted to also have a negative coefficient. The third secondary explanatory variable is the gross domestic savings rate as a percentage of GDP and was chosen due to its prominence as a consideration in well-cited literature. This variable is predicted to have a positive coefficient since higher savings allows for stronger income security which in turn should boost GNI per capita – a factor of HDI. The fourth secondary explanatory variable is a measure of political instability from the Worldwide Governance Indicators. It is a normally distributed measure with a target mean of 0 and standard deviation of 1. This measure attempts to capture a country's level of political stability and absence of politically motivated violence. This variable is included as political instability is a factor of theoretical human development, and it is predicted to have a positive coefficient as lower political instability fosters human development. The fifth and final secondary explanatory variable is a dummy variable to identify countries that are a member of the OECD. The country receives a 1 if they are a member and 0 if they are not a member. This is to examine how income inequality may affect globalized nations differently. OECD countries are predicted to have much higher HDI levels as they are developed countries with strong international trade presences.

Variable	**Description**	**Units**	**Year**	**Source**
HDI	Country's Human Development Index	Percentage	2018	UNDP
Gini	Country's Gini coefficient	Percentage	2010 – 17	UNDP
povRate	Percentage of population below international poverty line	Percentage	2011 – 18	WHO
popGrow	Population growth of country	Percentage	2018	World Bank
saveRate	Gross domestic savings as percentage of GDP	Percentage	2018	World Bank
polInstab	Country's political stability and absence of politically motivated violence	Standard Normal Distribution	2018	World Bank
OECD	Whether or not a country is in the OECD	1 if member 0 if not	2018	OECD

Table 3.1

Variable	Observations	Mean	Std. Deviation	Min	Max
HDI	189	71.34	15.08	37.66	95.34
Gini	151	38.12	7.69	25	63
povRate	140	12.25	18.86	0	77.6
popGrow	187	1.29	1.15	-1.80	4.92
saveRate	161	20.14	16.75	-50.69	60.70
polInstab	188	-.08	.97	-2.99	1.54
OECD	189	.19	.39	0	1

Table 3.2

Table 3.1 displays a summary of the variables. Table 3.2 displays the variable's descriptive statistics.

In order to find an unbiased estimation of the parameter coefficients in ordinary least squares regression, the following assumptions were made with supporting evidence for the multiple linear regression (MLR) models. MLR 1 – the model is linear in parameters. All models from section IV are linear in parameters, so this assumption holds. MLR 2 – the model is based on random sampling. Data was collected from every country possible, meaning no countries were purposely excluded. Therefore, this assumption holds. The list of countries included can be found in Appendix A. MLR 3 – no exact linear relationships between explanatory variables. All of the explanatory variables were carefully selected to ensure there is no perfect collinearity. The table with all of the correlation coefficients between the variables proving this fact can be found in Appendix B, so this assumption holds. MLR 4 – the error term has an expected value of zero given any explanatory variable. This assumption is difficult to concretely prove true since the exact population model is unknown. This paper will assume MLR 4 but consider the possibility of misspecified models and unobserved factors in every regression analysis. MLR 5 – error has the same variance given any explanatory variable. This assumption is also difficult to concretely prove true since the exact variance of error is unknown. This paper will assume MLR 5 but consider the possibility of heteroskedacity due to variance depending on unobserved factors beyond the explanatory variables examined in the models. This completes the five Gauss-Markov assumptions. MLR 6 – the population error is independent of the explanatory variables and normally distributed about 0. Several variables actually break this assumption as HDI and Gini take on values only between 0 and 100 and OECD is either 0 or 1. However, this paper will continue forward and assume MLR 6 in order to provide more robust analysis while not forgetting the fact that MLR 6 is technically not satisfied. With MLR 1 through MLR 6 having been considered, this satisfies the Classical Linear Model assumptions.

IV. Results

All of the following regression models have been created in STATA and can be found in more detail in Appendix C.

Model 1

This is a simple linear regression model to show the ceteris paribus effect of income inequality on human development without additional variables. The dependent variable is *HDI* and the explanatory variable is *Gini*.

$$\textit{Model 1:}\ HDI = \beta_0 + \beta_1(Gini) + u$$

From the STATA output, the coefficients are as follows.

$$\textit{Estimated Equation 1:}\ HDI = 102.25 - .84\ (Gini)$$

As predicted, the coefficient on the *Gini* has a negative sign meaning that increased income inequality as measured through the Gini coefficient causes a decrease in human development as measured through the HDI. More specifically, this model can be interpreted as a 1% increase in a country's Gini coefficient leads to a .84% decrease in a country's HDI. Here, the coefficient has a p-value of 0.00, so it has a significance at the 1% level and even the .1% level. This means that the Gini coefficient is very likely to at least have some effect on HDI. The nearly-zero p-value leads to a tight 95% confidence interval for this coefficient: [-1.14, -.54]. This means that there is a 95% chance that the coefficient falls within this range based on the simple regression. The intercept in this model of 102.25 may be interpreted as what the HDI value would be in the absence of any income inequality – a 0 for the Gini coefficient. This is only theoretical though as it is essentially impossible for a perfectly even distribution of income. While this model uses 151 observations which is a strong amount of the total sample size (189), it only has an R-squared value of .1687. This means that the model explains 16.87% of variation in *HDI*, so the correlation between these two values is weak. This simple linear regression model is likely not fully explaining the ceteris paribus effect of income inequality and human development due to missing additional key explanatory variables. This can be a starting point for understanding the basic relationship between income inequality and human development.

Model 2

This model is a multiple linear regression model. The dependent variable is *HDI* and the explanatory variables are *Gini*, *povRate*, *popGrow*, *saveRate*, and *polInstab*.

$$\textit{Model 2:}\ HDI = \beta_0 + \beta_1(Gini) + \beta_2(povRate) + \beta_3(popGrow) + \beta_4(saveRate) + \beta_5(polInstab) + u$$

From the STATA output, the coefficients are as follows.

$$\textit{Estimated Equation 2: } HDI = 82.85 - .18\,(Gini) - .31\,(povRate) - 3.29(popGrow) + .23\,(saveRate) + 5.88\,(polInstab)$$

As predicted, the coefficient on *Gini* still has a negative sign along with *povRate* and *popGrow*. This means that increased income inequality as measured through the Gini coefficient, increased poverty levels, and increased population growth all have a negative impact on human development. More specifically, this model can be interpreted as a 1% increase in a country's Gini coefficient leads to a .18% decrease in a country's HDI. A 1% increase in a country's poverty level leads to a .31% decrease in a country's HDI. Thirdly, a 1% increase in a country's population growth leads to a 3.29% decrease in a country's HDI. It is interesting to note that the coefficient on *Gini* increased from Model 1, meaning that the Gini coefficient may have less of an impact on HDI when there are other factors considered. On the other hand, the coefficients on *saveRate* and *polInstab* both have a positive sign, meaning increased savings rates and increased political stability lead to higher levels of human development. To specify, a 1% increase in a country's savings rate leads to a .23% increase in a country's HDI. Lastly, a 1-point increase in a country's political stability leads to a 5.88% increase in a country's HDI. This coefficient is so large since a 1-point increase on a normal distribution can be a significant increase in stability. If the company moves from a rating of 0 to 1, the country is actually improving to be more stable than an additional 34% of countries – a very large amount. Another interesting piece to note is that all of four of the secondary explanatory variables have a p-value of 0.00. This means all four of these variables are statistically significant at the highest level and therefore almost undoubtably have an effect on HDI. As for *Gini*, t-statistic is -1.93, so it is significant on a two-sided test at the 10% level. The coefficient has a .056 p-value, so it is nearly significant at the 5% level but not quite. This significance drops from Model 1 which may mean that income inequality has less of an impact on human development than initially thought when several other factors are held constant. Additionally, the 95% confidence interval for *Gini* is tighter but closer to zero than in Model 1 with it now being [-.36, 0.00]. This tighter interval may mean that the exact ceteris paribus effect of income inequality on human development is closer to being uncovered. Furthermore, this model uses 129 observations, less than Model 1, but still enough observations for sufficient analysis. It has a much higher R-squared value of .7889 compared to Model 1's R-squared value of .1649. Again, this means that Model 2 explains 78.89% of variation in *HDI*, so the fit of this model is strong. This multiple linear regression model is a step in the right direction to explaining the ceteris paribus effect of income inequality and human development, but it may be overfitting the model as the R-squared value is quite high.

A summary of all regression models can be found below in Table 4.1.

Dependent Variable: *HDI*				
Explanatory Variables	Model 1	Model 2	Model 3	Model 4
Gini	-.84*** (.15)	-.18* (.09)	-.03 (.08)	-1.10 (.67)
povRate		-.31*** (.05)	-.32*** (.04)	-.32*** (.05)
popGrow		-3.29*** (.74)	-2.73*** (.63)	-3.20*** (.74)
saveRate		.23*** (.05)	.17*** (.04)	.23*** (.05)
polInstab		5.88*** (.84)	3.65*** (.78)	5.67*** (.85)
OECD			10.97*** (1.56)	
Gini2				.01 (.01)
Intercept	102.25*** (5.92)	82.85*** (3.48)	74.60*** (3.18)	100.75*** (13.26)
Observations	151	129	129	129
R-squared	.17	.79	.85	.79

Table 4.1

Significant at * 10% ** 5% *** 1%

V. Extensions

All of the following regression models have been created in STATA and can be found in more detail in Appendix C unless otherwise stated.

<u>Model 3</u>

This model is a multiple linear regression model. The dependent variable is *HDI* and the explanatory variables are *Gini*, *povRate*, *popGrow*, *saveRate*, *polInstab*, and *OECD*. *OECD* is a dummy variable taking on the form 1 if the country is a member of the OECD and 0 if not.

$$\text{Model 3: } HDI = \beta_0 + \beta_1(Gini) + \beta_2(povRate) + \beta_3(popGrow) + \beta_4(saveRate) + \beta_5(polInstab) + \beta_6(OECD) + u$$

From the STATA output, the coefficients are as follows.

$$\text{Estimated Equation 3: } HDI = 74.60 - .03\ (Gini) - .32\ (povRate) - 2.73(popGrow) + .17\ (saveRate) + 3.65\ (polInstab) + 10.97\ (OECD)$$

This model differs from Model 2 in that a dummy variable *OECD* has been introduced. This dummy variable allows for a comparison of regressions for countries that are a member of OECD against countries that are not. In this model, the dummy variable has been brought in as an intercept change. From the estimated equation, countries that are a member of the OECD have, on average, 10.97% increase in HDI compared to other countries. This is quite a large shift, yet it makes sense as these countries emphasize international cooperation and have strict standards for membership. Additionally, all of the coefficients on the explanatory variables, except *povRate*, have a smaller magnitude than in Model 2 indicating that these factors have less of an impact when considering whether or not the country embraces international cooperation to the extent of membership in OECD. All of the secondary explanatory variables have p-value of 0.00, so they are all statistically significant at the 1% level. However, the most interesting change in this model is *OECD*'s effect on *Gini*. The coefficient increases to -.03 meaning that a 1% change in a country's Gini coefficient leads to a mere .03% decrease in a country's HDI. On top of that, this coefficient's standard error is .08, so it has a t-statistic of -.33. This incredibly near-zero t-statistic leads to *Gini* no longer being statistically significant at any relevant level which may signal income inequality's limited to no impact on human development. This model has an R-squared value of .85 which means a very strong goodness of fit.

<u>Model 4</u>

Now, this paper will examine an alternate functional form of Model 2. The change in functional form comes in to play as having a term for the Gini coefficient squared. *Gini2* is simply the country's Gini coefficient squared. This is to better examine the marginal effect of income inequality on human development. Additionally, this new model will explore Kuznet's hypothesis as countries in a later phase of development have lower income inequality levels per Kuznet's hypothesis. This model is a multiple linear regression model. The dependent variable is *HDI* and the explanatory variables are *Gini*, *povRate*, *popGrow*, *saveRate*, *polInstab*, and *Gini2*.

$$\textit{Model 4:}\ \ HDI\ = \beta_0 + \ \beta_1(Gini) + \ \beta_2(povRate) + \ \beta_3(popGrow) + \ \beta_4(saveRate) + \beta_5(polInstab) + \beta_6(Gini2) + \ u$$

From the STATA output, the coefficients are as follows.

$$\textit{Estimated Equation 4:}\ HDI\ = \ 100.75 - \ 1.10\ (Gini) - \ .32\ (povRate) - 3.20\ (popGrow) + .23\ (saveRate) + \ 5.67\ (polInstab) + .01\ (Gini2)$$

In this model, all of the coefficients from previous models have consistent signs. However, the new coefficient, *Gini2,* has a positive sign indicating that there is a diminishing marginal effect of income inequality on human development. As income inequality grows larger and larger, its effect on human development is supposedly not as strong. The R-squared value is .79 which equals the goodness of fit from Model 2. However, one change from Model 2 is the fact that *Gini* and *Gini2* have p-values of .102 and .164 respectively. This indicates that neither variable is significant at the 10% level, though *Gini* is incredibly close. This lack of significance may be due to collinearity since the two variables have a relatively high correlation. To test whether in fact these two variables in combination have any significance at all on human development, this paper will perform an F-Test to test the joint significance of *Gini* and *Gini2*.

$$H_0\text{: } \beta_1 = 0, \beta_6 = 0$$

$$H_1\text{: } H_0 \text{ is false}$$

The STATA output of the unrestricted model can be found in Appendix D. From this, the F-Statistic was calculated to be 2.73. The critical value for $F_{2,\,129}$ at 10% is 2.30, and the critical value for $F_{2,\,129}$ at 5% is 3.00. The calculated F values is not within the rejection region for 5%, but it is within the rejection region for 10%. Thus, we reject the null hypothesis at the 10% significance level. This means that the two variables have a joint significance at the 10% level. Together, these measures of income inequality likely do have some impact on human development – a new finding compared to a simpler t-test. Again, they may have been separately insignificant due to multicollinearity, but this F-test allows us to examine them without that concern.

VI. Conclusions

After analyzing all four models, our initial hypothesis was correct in that income inequality has a negative effect on human development as the coefficients were all negative. However, it is important to consider the fact that the Gini coefficient did not have statistical significance when the dummy variable to represent countries that are a part of OECD was present. Also, without OECD but including a squared term for Gini, there was not an independent significance on those terms, but there was indeed joint significance for Gini and Gini squared after analyzing the results of the F-test. This may mean that across all countries, there is a trend between income inequality and level of human development, but perhaps when accounting for additional factors and holding them constant, that may lead to income inequality not truly have a causal effect on human development. However, this fact is still uncertain.

On the other hand, all of the secondary explanatory variables had strong significance across all four model. This indicates that poverty rates, population growth, savings rates, and political instability are quite likely factors to be included in the population model for estimating a country's human development index. As expected, higher levels of poverty and population growth had an adverse effect on human development, and high levels of savings and political stability had a beneficial effect on human development. These variables were brought into the models to better uncover the ceteris paribus effect of income inequality on human development. Since the coefficient on the Gini variable still varied from model to model, yet the exact effect is still unclear.

After understanding the results of the models in this paper, there may still be future research that brings in additional secondary explanatory variables. Factors like sustainability, social equality, and human rights have not fully been accounted for, despite being a piece of human development for many prominent researchers in the field. Additionally, it may be interesting to analyze how income inequality moves with human development over time. A time series analysis could be utilized on similar data sets in order to understand if the two variables have a relationship even over a long period of time. Overall, income inequality is an issue that persists across all modern societies – both developed and underdeveloped – while human development is a critical measure of how we can make the world a safer, more tolerant, and more equitable place for all to live.

VII. References

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VIII. Appendix

Appendix A: List of countries included in datasets.

Afghanistan Albania Algeria Andorra Angola Antigua and Barbuda Argentina Armenia Australia Austria Azerbaijan Bahamas Bahrain Bangladesh Barbados Belarus Belgium Belize Benin Bhutan Bolivia (Plurinational State of) Bosnia and Herzegovina Botswana Brazil Brunei Darussalam Bulgaria Burkina Faso Burundi Cabo Verde Cambodia Cameroon Canada Central African Republic Chad Chile China Colombia Comoros Congo Congo (Democratic Republic of the) Costa Rica Côte d'Ivoire Croatia Cuba Cyprus Czechia Denmark	Djibouti Dominica Dominican Republic Ecuador Egypt El Salvador Equatorial Guinea Eritrea Estonia Eswatini (Kingdom of) Ethiopia Fiji Finland France Gabon Gambia Georgia Germany Ghana Greece Grenada Guatemala Guinea Guinea-Bissau Guyana Haiti Honduras Hong Kong, China (SAR) Hungary Iceland India Indonesia Iran (Islamic Republic of) Iraq Ireland Israel Italy Jamaica Japan Jordan Kazakhstan Kenya Kiribati Korea (Republic of) Kuwait Kyrgyzstan Lao People's Democratic Republic Latvia	Lebanon Lesotho Liberia Libya Liechtenstein Lithuania Luxembourg Madagascar Malawi Malaysia Maldives Mali Malta Marshall Islands Mauritania Mauritius Mexico Micronesia (Federated States of) Moldova (Republic of) Mongolia Montenegro Morocco Mozambique Myanmar Namibia Nepal Netherlands New Zealand Nicaragua Niger Nigeria North Macedonia Norway Oman Pakistan Palau Palestine, State of Panama Papua New Guinea Paraguay Peru Philippines Poland Portugal Qatar Romania Russian Federation Rwanda	Saint Kitts and Nevis Sao Tome and Principe Saint Lucia Saint Vincent and the Grenadines Samoa Saudi Arabia Senegal Serbia Seychelles Sierra Leone Singapore Slovakia Slovenia Solomon Islands South Africa South Sudan Spain Sri Lanka Sudan Suriname Sweden Switzerland Syrian Arab Republic Tajikistan Tanzania (United Republic of) Thailand Timor-Leste Togo Tonga Trinidad and Tobago Tunisia Turkey Turkmenistan Uganda Ukraine United Arab Emirates United Kingdom United States Uruguay Uzbekistan Vanuatu Venezuela (Bolivarian Republic of) Viet Nam Yemen Zambia Zimbabwe

Appendix B: Correlation coefficients between each variable.

	HDI	*Gini*	*povRate*	*popGrow*	*saveRate*	*polInstab*	*OECD*
HDI	1.00						
Gini	-.42	1.00					
povRate	-.77	.40	1.00				
popGrow	-.64	.36	.62	1.00			
saveRate	.42	-.13	-.29	-.03	1.00		
polInstab	.63	-.19	-.39	-.35	.23	1.00	
OECD	.69	-.38	-.36	-.35	.30	.52	1.00

Appendix C: STATA regression outputs for all models.

Model 1

```
. regress HDI Gini

      Source |       SS           df       MS      Number of obs   =       151
-------------+----------------------------------   F(1, 149)       =     30.24
       Model |  6220.72643         1  6220.72643   Prob > F        =    0.0000
    Residual |  30654.2303       149  205.733089   R-squared       =    0.1687
-------------+----------------------------------   Adj R-squared   =    0.1631
       Total |  36874.9567       150  245.833045   Root MSE        =    14.343

------------------------------------------------------------------------------
         HDI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        Gini |  -.8377245   .1523466    -5.50   0.000    -1.138763   -.5366856
       _cons |   102.2504   5.922981    17.26   0.000      90.5465    113.9543
------------------------------------------------------------------------------
```

Model 2

```
. regress HDI Gini povRate popGrow saveRate PolInstab
```

Source	SS	df	MS
Model	24100.0489	5	4820.00977
Residual	6447.6765	123	52.4201342
Total	30547.7254	128	238.654104

Number of obs	=	129
F(5, 123)	=	91.95
Prob > F	=	0.0000
R-squared	=	0.7889
Adj R-squared	=	0.7804
Root MSE	=	7.2402

HDI	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Gini	-.1759573	.0910215	-1.93	0.056	-.3561288	.0042142
povRate	-.3145746	.0470964	-6.68	0.000	-.4077991	-.2213502
popGrow	-3.288149	.7364399	-4.46	0.000	-4.745887	-1.830412
saveRate	.2263005	.0471737	4.80	0.000	.132923	.319678
PolInstab	5.881097	.8430016	6.98	0.000	4.212427	7.549767
_cons	82.85396	3.482963	23.79	0.000	75.95965	89.74827

Model 3

```
. regress HDI Gini povRate popGrow saveRate PolInstab OECD
```

Source	SS	df	MS
Model	25953.4861	6	4325.58102
Residual	4594.23924	122	37.6576987
Total	30547.7254	128	238.654104

Number of obs	=	129
F(6, 122)	=	114.87
Prob > F	=	0.0000
R-squared	=	0.8496
Adj R-squared	=	0.8422
Root MSE	=	6.1366

HDI	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Gini	-.0266741	.0800283	-0.33	0.739	-.1850981	.1317499
povRate	-.3203214	.0399261	-8.02	0.000	-.3993591	-.2412836
popGrow	-2.730388	.6292304	-4.34	0.000	-3.976012	-1.484763
saveRate	.1658563	.040901	4.06	0.000	.0848887	.2468239
PolInstab	3.647896	.7822072	4.66	0.000	2.099439	5.196354
OECD	10.97283	1.564072	7.02	0.000	7.876596	14.06907
_cons	74.5994	3.177913	23.47	0.000	68.3084	80.89039

Model 4

```
. regress HDI Gini povRate popGrow saveRate PolInstab Gini2
```

Source	SS	df	MS
Model	24201.8053	6	4033.63421
Residual	6345.92008	122	52.0157384
Total	30547.7254	128	238.654104

Number of obs	=	129
F(6, 122)	=	77.55
Prob > F	=	0.0000
R-squared	=	0.7923
Adj R-squared	=	0.7820
Root MSE	=	7.2122

HDI	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Gini	-1.101994	.6682661	-1.65	0.102	-2.424894	.2209053
povRate	-.3163099	.0469308	-6.74	0.000	-.409214	-.2234057
popGrow	-3.19896	.73636	-4.34	0.000	-4.656658	-1.741262
saveRate	.2281415	.0470098	4.85	0.000	.1350809	.3212022
PolInstab	5.666125	.8536934	6.64	0.000	3.976154	7.356097
Gini2	.0113898	.0081433	1.40	0.164	-.0047308	.0275104
_cons	100.7511	13.25787	7.60	0.000	74.50578	126.9963

Appendix D: STATA output for unrestricted model

```
. regress HDI povRate popGrow saveRate PolInstab
```

Source	SS	df	MS
Model	23904.1532	4	5976.0383
Residual	6643.57216	124	53.5771949
Total	30547.7254	128	238.654104

Number of obs	=	129
F(4, 124)	=	111.54
Prob > F	=	0.0000
R-squared	=	0.7825
Adj R-squared	=	0.7755
Root MSE	=	7.3196

HDI	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
povRate	-.3332967	.0465958	-7.15	0.000	-.4255227	-.2410706
popGrow	-3.518771	.7346893	-4.79	0.000	-4.972927	-2.064615
saveRate	.2305954	.0476386	4.84	0.000	.1363053	.3248856
PolInstab	5.888554	.8522456	6.91	0.000	4.201722	7.575387
_cons	76.62336	1.334718	57.41	0.000	73.98158	79.26514